Five year prediction of Sea Surface Temperature in the Tropical Atlantic: a comparison of simple statistical methods

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Abstract

We are developing schemes that predict future hurricane numbers by first predicting future sea surface temperatures (SSTs), and then apply the observed statistical relationship between SST and hurricane numbers. As part of this overall goal, in this study we compare the historical performance of three simple statistical methods for making five-year SST forecasts. We also present SST forecasts for 2006-2010 using these methods and compare them to forecasts made from two structural time series models.

1 Introduction

The number of hurricanes occurring in the Atlantic Ocean basin has increased in recent years, and this has led to considerable interest in trying to predict future levels of hurricane activity. One sector of society that is particularly interested in the number of hurricanes that may occur in the future is the insurance industry, which pays out large amounts of money when severe hurricanes make landfall in the US. The timescales over which this industry is most interested in forecasts of hurricane activity are, roughly speaking, a zero-to-two year timescale, for underwriters to set appropriate insurance rates, and a zero-to-five year timescale, to allow financial planners to ensure that their business has sufficient capital to withstand potential losses.

Motivated by this, we are in the process of building a set of models for the prediction of future hurricane numbers over these timescales. The models in our set are based on different methodologies and assumptions, in an attempt to understand how different methodologies and assumptions can impact the ultimate predictions. Within the set, one subset of methods is based on the idea of first predicting sea surface temperatures (SSTs), and then predicting hurricane numbers as a function of the predicted SSTs. The rationale for this approach is that there is a clear correlation between SST and hurricane numbers, such that greater numbers of hurricanes occur in years with warmer SSTs. How, then, should we predict SSTs in order to make hurricane number predictions on this basis?

Meagher and Jewson (2006) compared three simple statistical methods for the *one-year* forecasting of tropical Atlantic SST. Their results show that the relative skill levels of the forecasts produced by the different methods they consider is determined by a trade-off between bias and variance. Bias can be reduced by using a two parameter trend prediction model, but a one parameter model that ignores the trend has lower variance and ultimately gives better predictions when skill is measured using mean square error. How are these results likely to change as we move from considering one-year forecasts to considering five-year forecasts? For five year forecasts both bias and variance are likely to increase, but not necessarily in the same way, and as a result which model performs best might be expected to change compared to the results of Meagher and Jewson (2006). We therefore extend their study to investigate which methods and parameter sets perform best for five year predictions.

We also consider 2 new statistical models, known as 'local level' and 'local linear' models. These models are examples of so-called *structural time-series models* and are commonly used in Econometrics. We produce SST forecasts using these 2 additional methods, and compare the forecasts with those from our original set of 3 methods.

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2 Data

As in Meagher and Jewson (2006) we use the SST dataset HadISST (Rayner et al., 2002), which contains monthly mean SSTs from 1870 to 2005 on a 1^ox1^o grid. As in Meagher and Jewson (2006), we define a Main Development Region SST index as the average of the SSTs in the region (10^o-20^oN, 15^o-70^oW), although we differ from Meagher and Jewson (2006) in that we now use a July to September average rather than a June to November average. This is because July to September SSTs show a slightly higher correlation with annual hurricane numbers than the June to November SSTs.

The HadISST data is not updated in real-time, and so to update this dataset to the end of 2006 we use the NOAA Optimal Interpolation SST V2 data which is available from 1981 to the present. The July-September MDR index derived from the NOAA dataset is highly correlated with that derived from HADISST (with linear correlation coefficient of 0.98).

3 Method

Following Meagher and Jewson (2006) we compare three simple methods for predicting SST using back-testing on the MDR SST timeseries. Meagher and Jewson (2006) tested 1 year forecasts while we now test 1-5 year forecasts.

The basic 3 methods we use are:

1. Flat-line (FL): a trailing moving average
2. Linear trend (LT): a linear trend fitted to the data and extrapolated to predict the next five years
3. Damped linear trend (DLT): An 'optimal' combination of the flat-line and linear trend (originally from Jewson and Penzer (2004)).

We compare predictions from these methods with predictions from two structural time series prediction methods which are common in Econometrics (see for example Harvey and Shephard (1993)). These models are:

- a *local level* model, that assumes that the historic SST time series is a random walk plus noise.
- a *local linear trend* model, that assumes that the historic SST time series is a random walk plus random walk trend plus noise

The local level model has two parameters (the amplitude of the random walk and the amplitude of the noise) and captures the idea that the level of SST changes over time, but with some memory. The local linear trend model has three parameters (the amplitude of the basic random walk, the amplitude of the random walk for the trend, and the amplitude of noise) and additionally captures the idea that SST is influenced by a slowly changing trend. We fit the two structural time-series model to the historical data using maximum likelihood.

4 Results

4.1 Backtesting skill

To compare the three basic prediction methods, 5 year periods from 1911-1915 to 2001-2005 were predicted (or 'hindcasted') using from 5 to 40 years of prior data. Figure 1 shows the RMS error for all three models versus the number of years of prior data used. The upper left panel shows the score for 5-year forecasts, and the other five panels show the scores for separate forecasts for 1 to 5 years ahead.

Considering first the RMSE score for the 5-year forecast, we see that the flat-line model with a window length of 8-10 years performs best. Next best is the damped linear trend model for a window length of around 17 years. Worst of the three models is the linear trend model, which has an optimal window length of 24 years. The damped linear trend and linear trend models do very badly for short window lengths, because of the huge uncertainty in the trend parameters when estimated using so little data. Their performance is then very stable for window lengths longer than 13 years.

We now consider the forecasts for the individual years. First we note that the RMSE scores of these forecasts are scarcely lower than the RMSE score for the 5 year forecast. This is presumably because the ability of our simple methods to predict SST comes from the representation of long time-scale processes. Our methods do not capture any interannual time-scale phenomena. Second, we note that the optimal

window length for the flat-line forecast gradually reduces from 11 years to 7 years as the lead time increases. This is the expected behaviour of the flat-line model when used to model data with a weak trend.

To better understand the error behaviour of these prediction methods we decompose the RMSE into the bias and the standard deviation of the error. Figure 2 shows the bias for the three models and figure 3 their standard deviations. The flat line model shows a high bias which increases with the averaging period and the lead time. This is because using a flat-line cannot capture the trends in the data.

Figure 3 shows that it is the high variance in the predictions from the linear trend and damped linear trend models, presumably due to high parameter uncertainty, which is responsible for their poor performance when using small windows. The standard deviation of the flat line model error is close to independent of the lead time although we can see that the minimum is shifted to smaller window lengths for longer forecasts.

4.2 Sensitivity of the results to the hindcast period

One obvious question concerns the stability of our results with respect to the hindcast data we have used. Understanding this should give us some indication of the robustness of future forecasts. To check this stability we apply a bootstrap technique by calculating the window-length dependent RMSE on bootstrap samples of forecast years. Figure 4 shows the results for the five year forecast based on 1000 bootstrap samples. The left panel shows the frequency in which one method outperforms the other two methods, and the other panels show the distribution of optimal window lengths for the three methods. For a five year forecast the flat line method with a window length of 8 years is the best in almost all cases. In contrast, the optimal window length of the linear methods is strongly dependent on the hindcast years used. However we note that this is not necessarily a problem since the minima in the RMSE score for these methods is very shallow and therefore an imperfect window length does not greatly reduce the forecast quality.

Figure 5 shows the same experiment as the previous figure, but for a one year ahead forecast. Here the linear trend models outperform the flat line model in 40% of the bootstrap samples and the optimal window length of the flat line method is around 10 years, confirming the results given in Meagher and Jewson (2006).

4.3 Forecast for 2006-2010 and comparison to structural time series model forecasts

We now make forecasts for SST for the period 2006-2010 using the methods described above. Based on the backtesting results we use the flat line model with an 8 year window length, the linear trend model with a 24 year window and the damped linear trend model with a 17 year window.

In addition we make forecasts with the local level and local linear structural time series models. Point predictions from these models are the same as predictions from ARIMA(0,1,1) and ARIMA(0,2,2) models, although predicted error distributions are different.

Figure 6 shows the forecasts from the 3 simple methods, not including the structural models. As expected the linear trend models predict higher SSTs than the flat-line models. Curiously, the damped linear trend model actually predicts higher SSTs and a greater trend slope than the linear trend model. This is because it uses a shorter window length than the linear trend model. This unexpected behaviour slightly calls into question the way the damped linear trend model is constructed, and suggests that there may be other ways that one could construct such an optimal combination that might avoid this slightly awkward result. It also highlights the fact that the optimal window length for the linear trend models is not terribly well determined by the backtesting. Figure 7 also shows the predictions from the structural models. We see that these predictions lie between the predictions from the flat-line and linear trend models. Figure 8 shows the predictions from the 3 simple models, but now including (a) predicted RMSE scores for each model based on the backtesting results, and (b) a prediction for 2006 based on data up to the end of 2005. To estimate the 2006 MDR SST data we predict the July-September SST for 2006 using a linear model with the NOAA Optimal Interpolation SST July-August data as predictor ($1981 - 2005 : R^2 = 0.913$). This point forecast and 90% confidence intervals are plotted in the figure as a grey box.

5 Discussion

We have tested a number of simple statistical prediction schemes on historical SST data for the tropical Atlantic to evaluate their forecast quality for a five year ahead SST forecast. Our results are similar to

those of Meagher and Jewson (2006), who tested the same prediction methods for year-ahead forecasting. The flat line method, a trailing moving average, performed best using a window length of 8 years, which is slightly lower than the optimal window length for year-ahead forecasts. Next best was the damped linear trend method with window lengths around 17 years. The linear trend method shows no advantage over flat-line and damped linear trend for any forecast periods or window length. By applying the hindcast experiment on subsets of hindcast data we have shown that for the five year forecast the flat line methods nearly always outperform the linear trend methods whereas for a one year ahead forecast the linear methods are sometimes more accurate.

It is worth remarking that the five year ahead forecasts we have described have only around 10% higher uncertainty than the one year ahead forecast. It is likely that the one year ahead forecast can be improved significantly by including additional information such as the ENSO state, but for the five year ahead forecast the simple methods we have presented will be more difficult to beat.

We have presented 5 year forecasts from both these simple methods and local level and local linear trend structural time series models. The forecasts from these structural time-series methods lie in-between the flat line and linear trend forecasts and this suggests that one might consider the flat line and linear trend forecasts as lower and upper bounds.

One final but important point is that our backtesting study has compared the performance of forecast methods on average over the historical data. Are methods that have worked well over the period covered by the historical data likely to work well in the future? Not necessarily, since we seem to be in a period of rapid warming. Although there are similar periods of rapid warming in the historical data, there are also periods of cooling, and our backtesting results reflect some kind of average performance over the two. If we believe that the current warming will continue, then the methods that incorporate information about the trend may do better than they have done over the historical period, and the methods that ignore the trend may do worse than they have done over the historical period.

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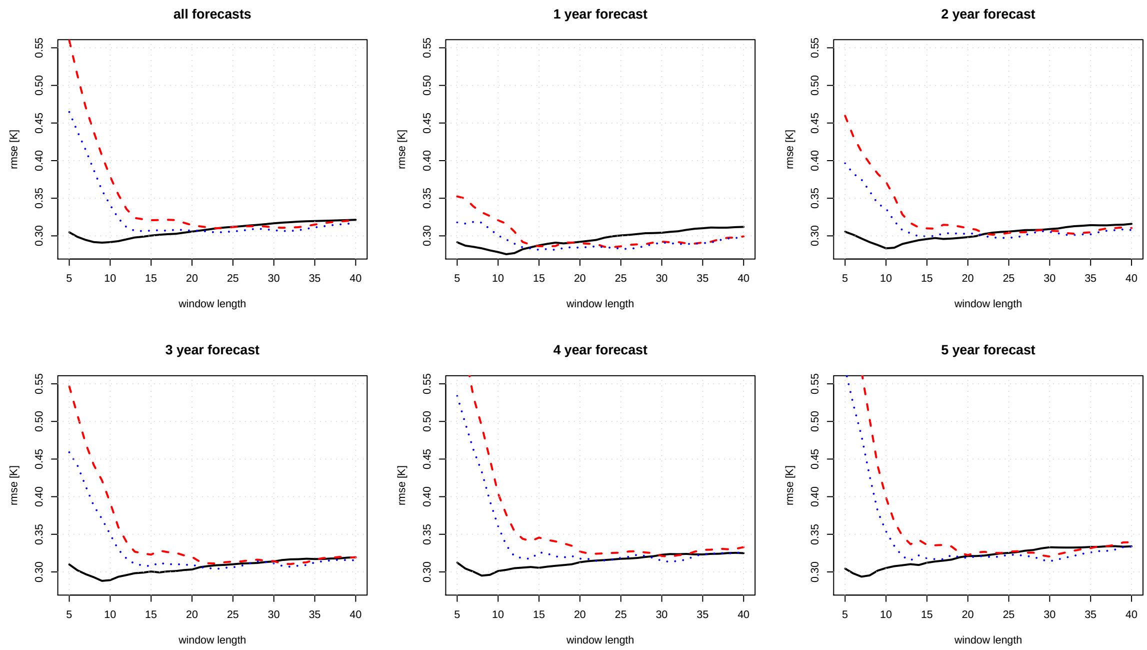


Figure 1: forecast RMSE for the flat line model (black solid), linear trend model (red dashed) and damped linear trend model (blue dotted) plotted against the window length; the upper left panel shows the RMSE over all forecast periods, the remaining panels show the RMSE for specific forecast times.

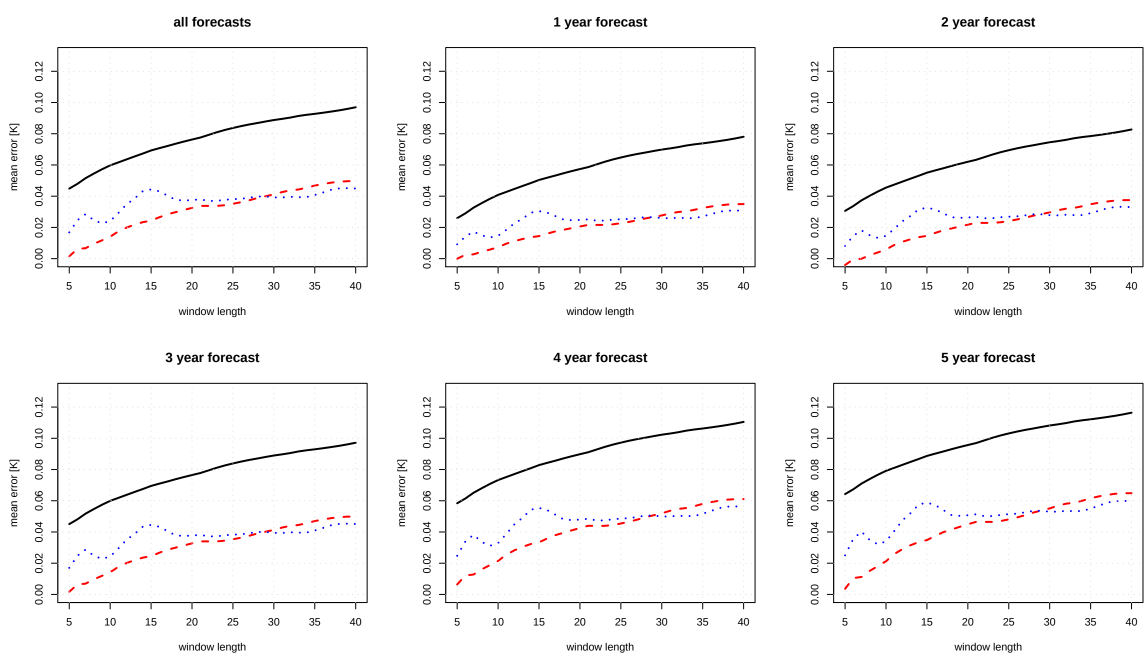


Figure 2: forecast bias for the flat line model (black solid), linear trend model (red dashed) and damped linear trend model (blue dotted) plotted against the window length; the upper left panel shows the mean bias over all forecast periods, the remaining panels show the bias for specific forecast times.

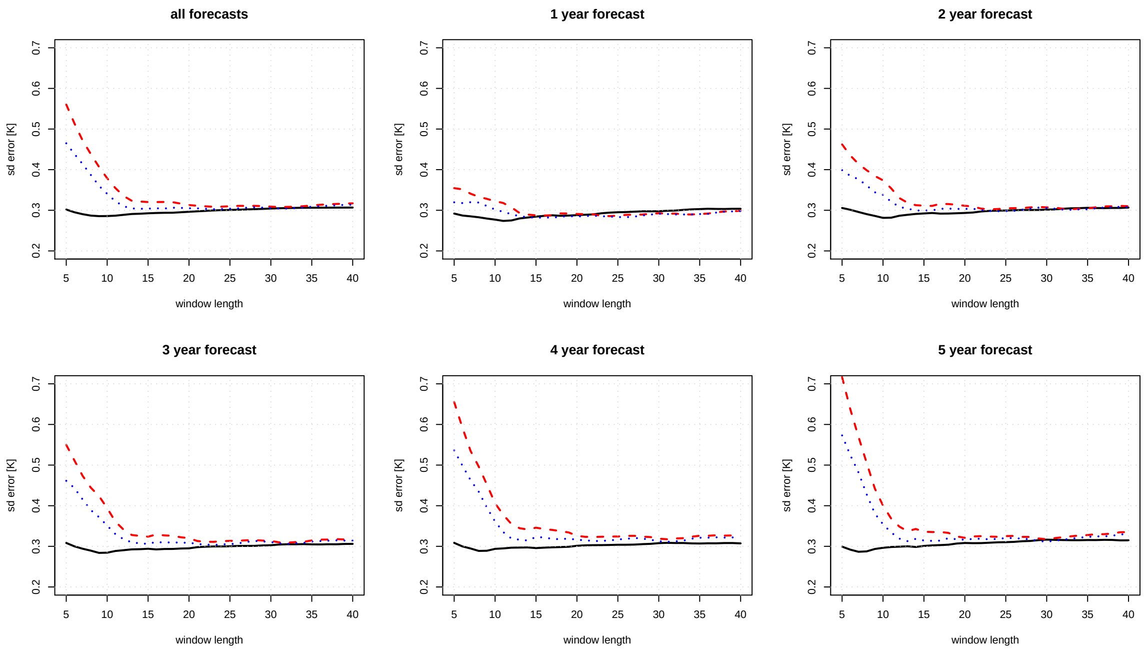


Figure 3: standard deviation of the forecast error for the flat line model (black solid), linear trend model (red dashed) and damped linear trend model (blue dotted) plotted against the window length; the upper left panel shows the SD error calculated over all hindcasts and forecast periods, the remaining panels show the SD error for specific forecast times.

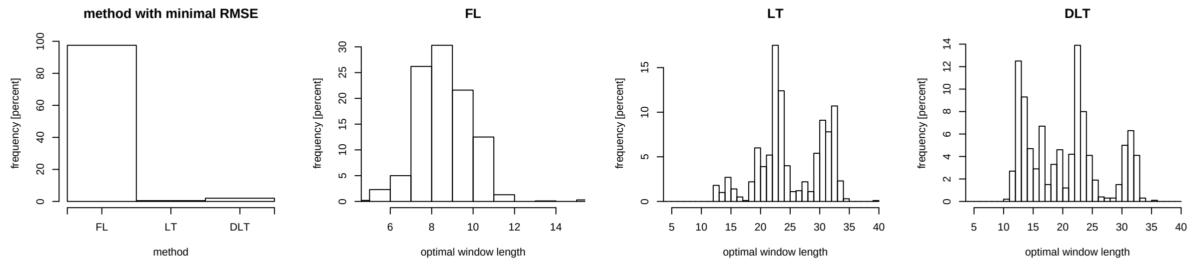


Figure 4: sensitivity to the hindcast period for 5yr forecasts as determined by bootstrap. From left to right; percentage of hindcast year samples in which a specific method performed the best, distribution of optimal window lengths for the flat line method, linear trend method and damped linear trend method.

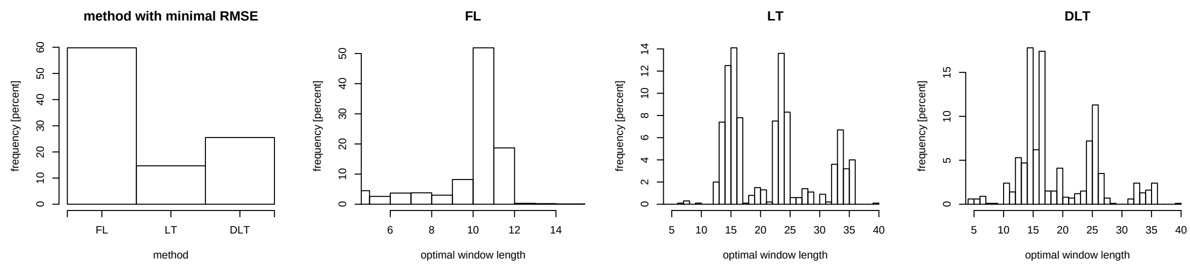


Figure 5: sensitivity to the hindcast period for 1yr forecasts as determined by bootstrap. From left to right; percentage of hindcast year samples in which a specific method performed the best, distribution of optimal window lengths for the flat line method, linear trend method and damped linear trend method.

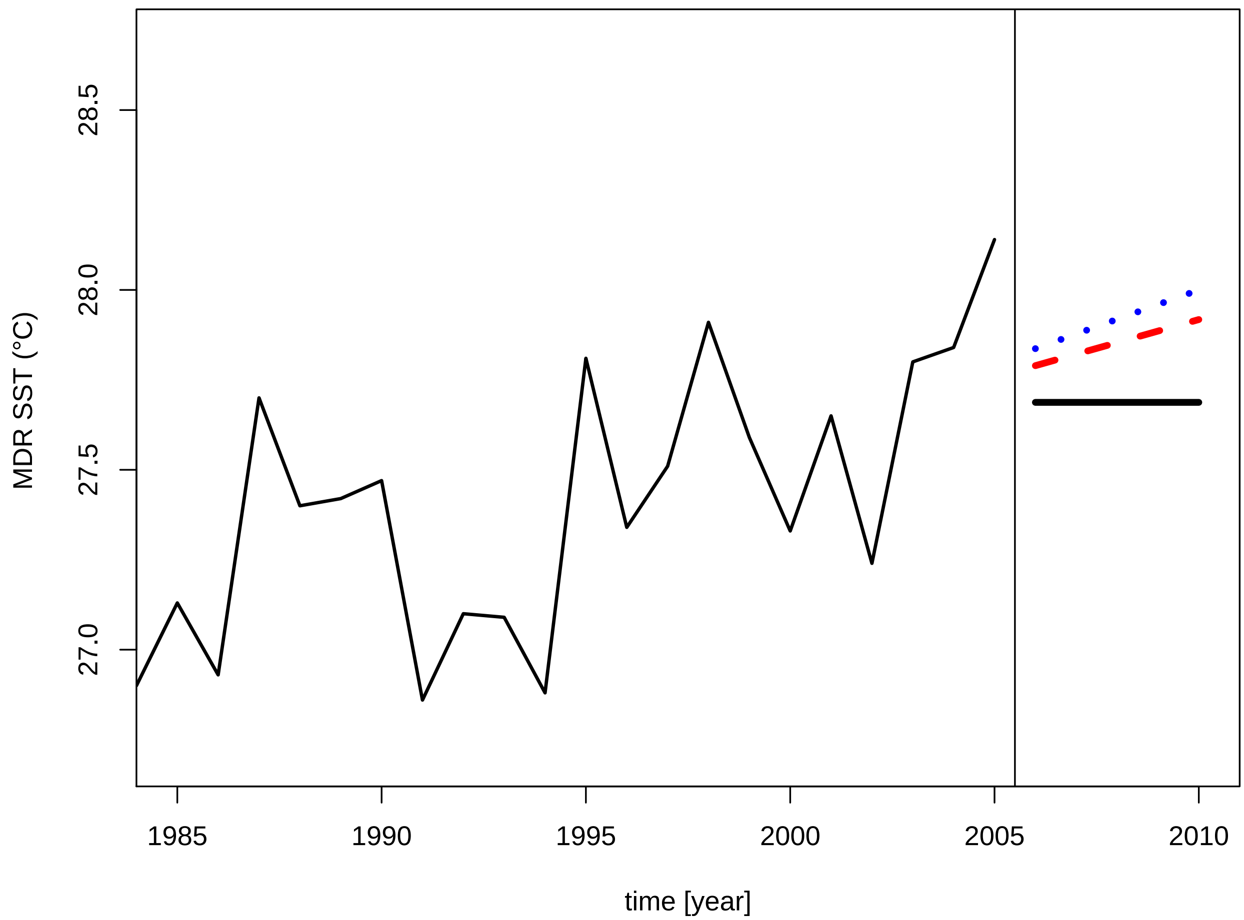


Figure 6: Comparison of the 3 simple statistical forecasts for 2006-2010 and their predicted RMSE. Flat-line (solid), linear trend (dashed) and damped linear trend (dotted).

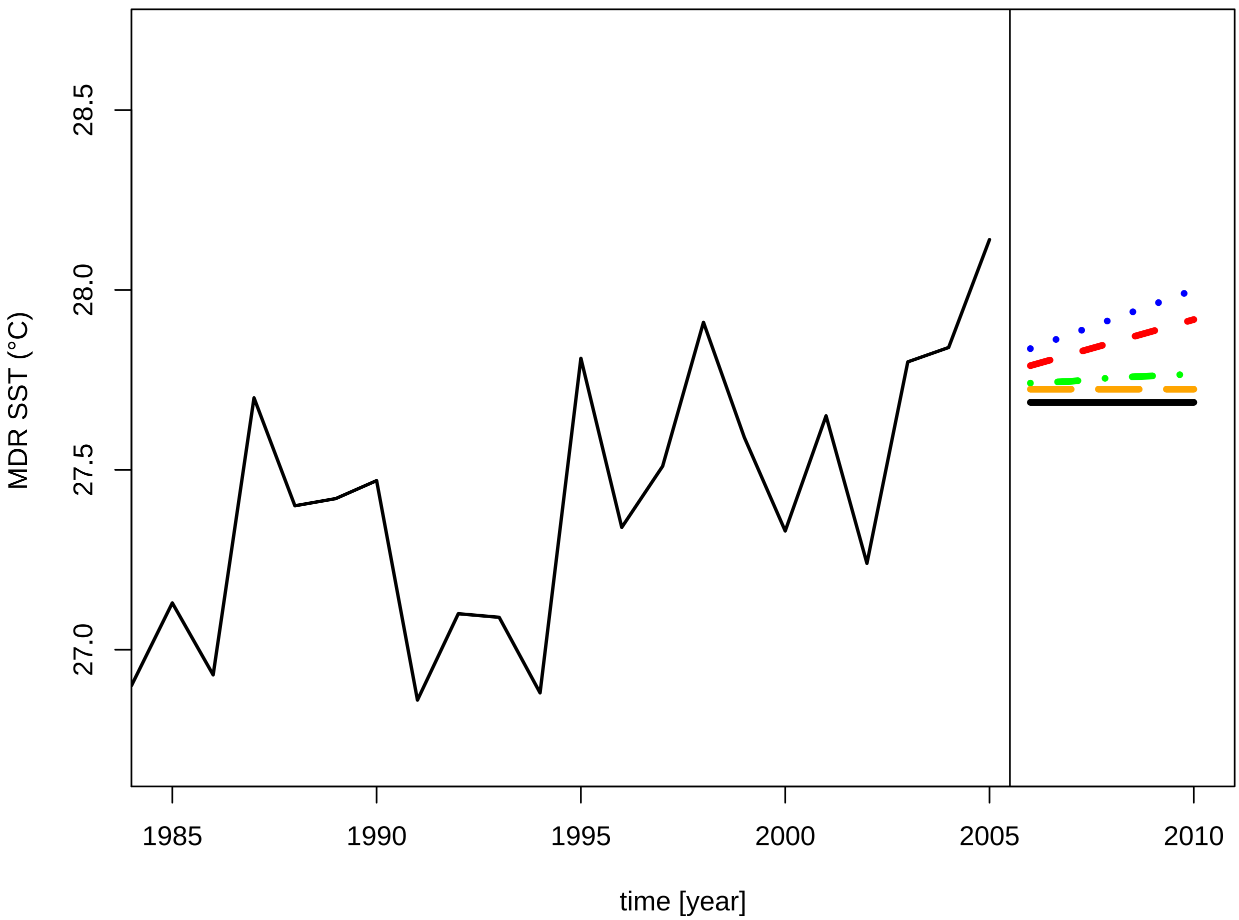


Figure 7: As in figure 6, but including predictions from the local level (long dashes) and local linear (dot-dashed) models.

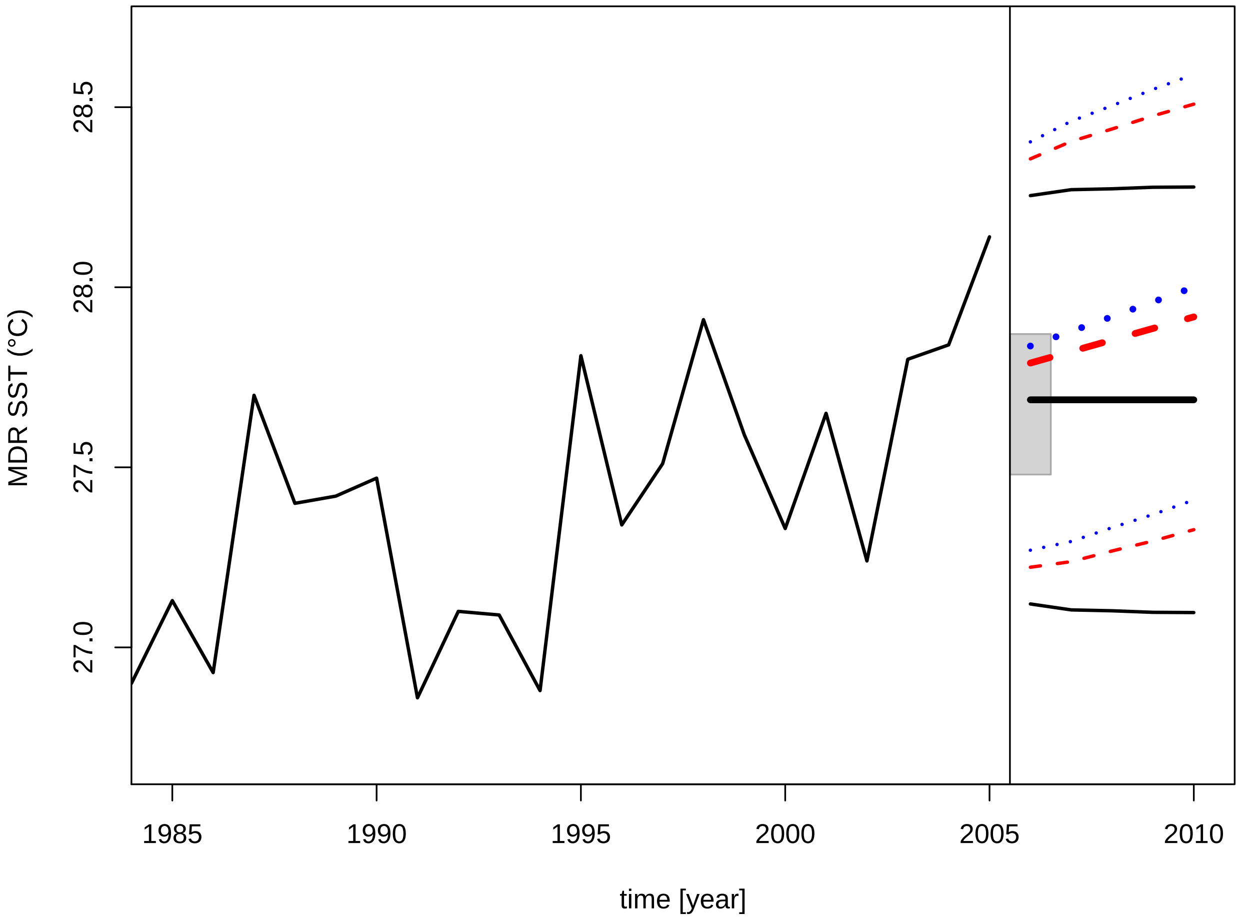
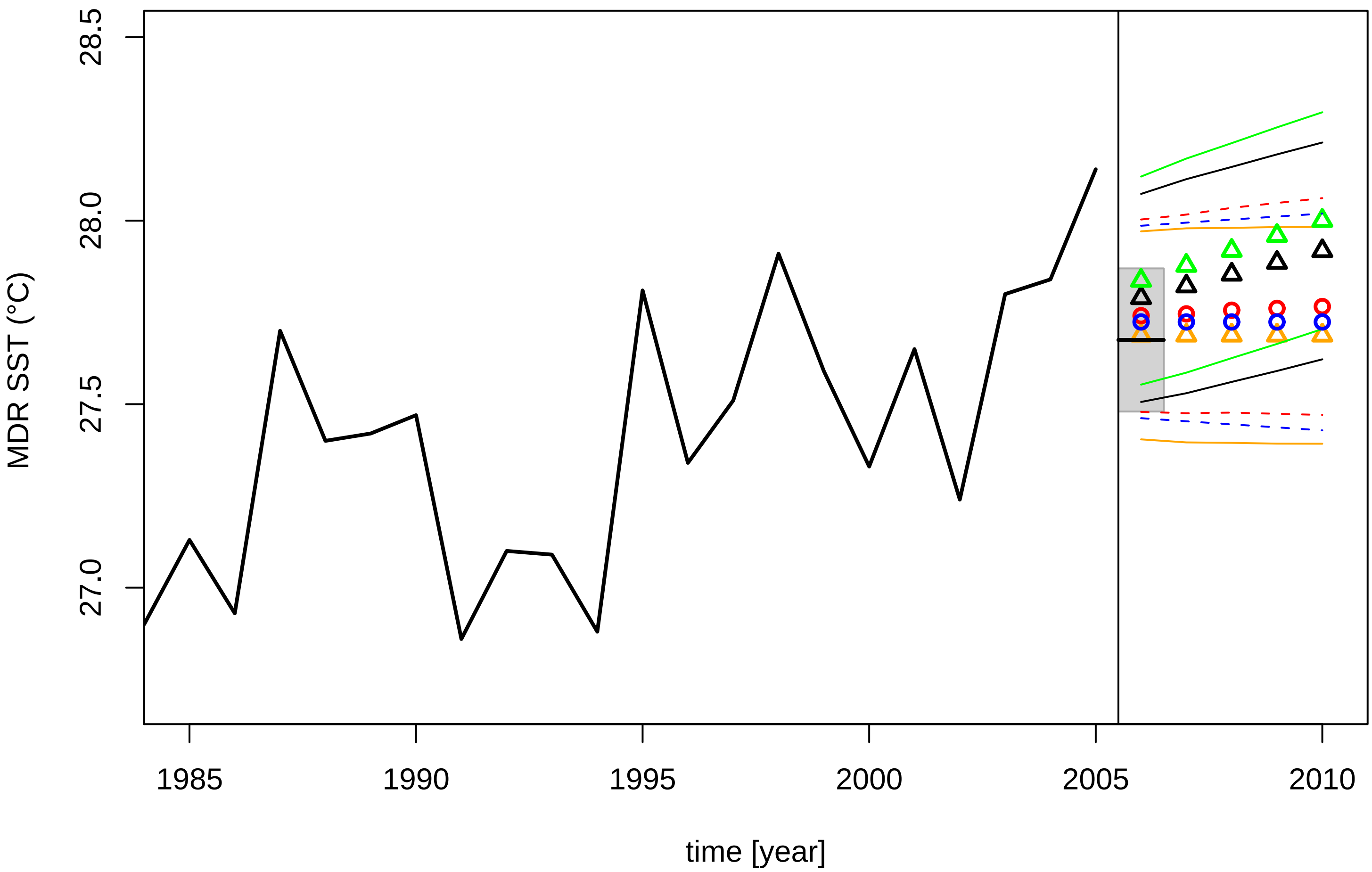


Figure 8: As in figure 6, but including (a) error bars showing plus/minus 1 standard deviation and (b) a forecast for 2006, with 90% confidence interval (grey box).



28.5
28.0
27.5
27.0
MDR SST (°C)
1985
1990
1995
2000
2005
2010
time [year]